© December 2025| IJIRT | Volume 12 Issue 7 | ISSN: 2349-6002

Comparative Analysis Using ML and DL Models for Time Series stock price prediction

Dr. Hemanth T S[1], Dr. Ramesh B[2], Chandana H.R[3], Divyashree H A[4], Yuktha Mukhi S P[5], Haleema Shadiya[6]

[1]*Associate Professor, Department of Computer Science and Business System, Malnad College of Engineering, Hassan, India*

[2]*Professor and HOD, Department of Computer Science and Business System, Malnad College of Engineering, Hassan, India*

[3,4,5,6]*Department of Computer Science and Business System, Malnad College of Engineering, Hassan, India*

***Abstract*- Stock market forecasting has been a hard issue since data- driven strategies appeared. Vital methods for forecasting stocks are DL and ML, which have turned into time-series modeling. In this review article, ML and DL models are compared and discussed in detail. Strengths, weak points, discusses, also Applications within real-world finance forecasting. The models that are classical in ML regress in a linear way. A random forest and a support vector machine are examples. Classical models in DL do include recurrent neural networks as well as long short term memory plus gated recurrent units This endeavor gives the perceptions under which models prove most effective. It highlights different market conditions and also scenarios about data.**

Key words include Machine Learning (ML), Deep Learning (DL), Linear Regression, Decision Tree, Random Forest, Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN).

I. INTRODUCTION

This collection of research explores diverse ML and DL techniques with Linear Regression and Decision Trees to more advanced models like Random Forest, XG Boost, LSTM, GRU, CNN, and Reinforcement Learning (Q- Learning and DQN). Some works deal with time-series forecasting based on past price as well as volume data. For the improved predictions, others incorporate technical indicators, sentiment analysis, and also news headlines.

A number of comparative analyses point out the merits and drawbacks of single models. For example, Random Forest generally demonstrates excellent accuracy in short-term prediction tasks, whereas GRU and LSTM networks are best at extracting sequential patterns in time-series data. Then again, hybrid and ensemble methods—uniting ML with DL— are revealed to be more effective than single-model schemes.

In addition to the advancement, the papers also point out significant areas of research work required, for example, improved interpretability of models, fusion of real-time and sentiment information, and effective deployment in trading platforms. Overall, this body of work indicates the increasing capability of AI to influence wiser, more data-driven financial decision-making

II. LITERATURE SURVEY

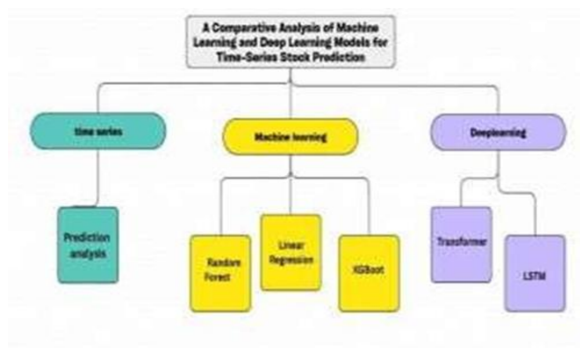

FIG 1: Types of key words

From [20] Kuo Y. et.al shows the survey about the the keywords used in the paper and fig [1] explains about that

A. DEEP LEARNING

Long Short-Term Memory (LSTM) networks also are widely used in order to precisely predict closing price as well as people talk about them since they can learn time-series data. Their disadvantages of following non-stationary data as well as learning long trends are yet discussed too. From Kuo Y. et.al there is a reveal about a survey regarding all of the paper's keywords. Fig [1] describes results from that same survey.

Transformer: A cutting-edge architecture originally designed for NLP but increasingly used in financial modeling. It handles long-term dependencies better than RNNs or LSTMs and allows parallel training. Useful in complex market trend analysis

B. Machine learning

Random Forest is utilized and compared for stock price prediction, often performing well in comparative studies.

Linear Regression: A simple model which estimates the stock prices under the assumption of linearity in input features (e.g., volume, last price) and the output (price in the future). Easy and understandable, but not suitable for depicting market fluctuations.

C. Time series

Prediction Analysis: Refers to analyzing historical stock price patterns to forecast future movements. Time-series methods often involve analyzing trends, seasonality, and autocorrelation. This may involve classical models like ARIMA or moving averages, but in this diagram it supports the modern ML/DL approach.

III. METHODOLOGY

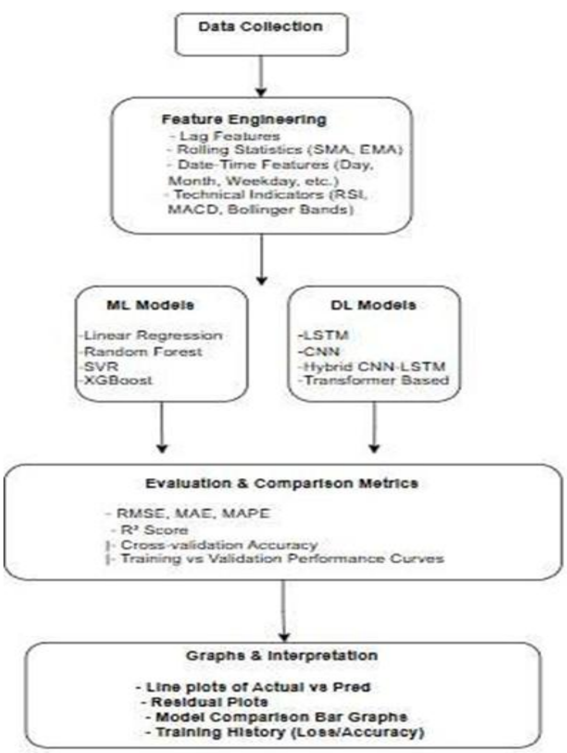

FIG 2: Structure of system methodology

Based on [12] E. F. Fama the system structure of methodology [fig 2]. this information provides explanation of the system

A. Dataset Collection

Historical stock prices (Open, High, Low, Close, Volume) are fetched from public sources such as Kaggle and Yahoo Finance for chosen companies or indices

B. Data Preprocessing

Data is sorted chronologically, missing values are handled, and features are normalized using scaling techniques like Min Max Scaler or Standard Scaler.

C. Feature Engineering

Lag features, rolling statistics (SMA, EMA), and technical indicators (MACD, RSI, Bollinger Bands) are created to capture market trends and momentum.

D. Data Validation

The dataset is checked for inconsistencies, outliers, or missing timestamps; any anomalies are cleaned or corrected to ensure data integrity.

E. Feature Extraction using DL

Lag features, rolling stats (SMA, EMA), and technical indicators (MACD, RSI, Bollinger Bands) are generated to identify market trends and momentum.

F. Model Building

Separate pipelines are developed for DL models (e.g., LSTM, CNN, Transformer-based) and ML models (e.g., Random Forest).

G. Model Training

All models are trained using historical data to forecast future stock prices, where DL models are trained using sequence input and ML models trained on tabular features

H. Evaluation and Hyperparameter Tuning

RMSE MAE MAPE and also R^2 are each metrics intended for the evaluating of model performance. For optimal performance, hyperparameters (e.g., learning rate, tree depth, epochs) get tuned.

I. Testing

Models are tested on unseen test data to assess generalization and robustness in predicting stock trends.

J. Prediction

Each model predicts future stock prices or the next-day closing price, based on historical input data.

K. Output

Results are presented through line plots (Actual vs Predicted), error metrics tables, and comparison graphs to highlight the best-performing models.

IV. RESEARCH GAP

1. Models Used

The majority of the studies employ individual models such as Linear Regression, SVM, Decision Trees, LSTM, etc.

2. Data Sources

There exists a shortage in investigating hybrid models coupling ML and DL (e.g., CNN-LSTM, GRU-XG Boost). Research relies heavily on historical price/volume data from platforms like Yahoo Finance. There's minimal use of real- time data and external signals like macroeconomic indicators or social sentiment.

3. Feature Engineering

Simple features are utilized such as with Moving Averages, and with both RSI and MACD. Most studies improving model accuracy and interpretability are not leveraging advanced feature selection and ranking methods.

4. Sentiment Analysis

Some use is made of social media or news sentiment, but more sophisticated NLP models (e.g., BERT, Fin BERT) for financial-specific sentiment analysis are rarely applied.

5. Evaluation Metrics

Accuracy-based metrics like MSE and RMSE dominate. However, financial performance metrics such as Sharpe Ratio or ROI are often ignored, limiting the practical relevance.

6. Model Explainability

Many models (especially LSTM, GRU) are black boxes. There's a need for explainable AI tools like SHAP or LIME to build trust in financial predictions.

7. Reinforcement Learning

RL is used experimentally (e.g., Q-learning, DQN), but there's a gap in applying robust RL strategies for real- world, multi-asset trading systems.

8. Practical Deployment

Most studies remain theoretical. There's limited effort toward real-time deployment, mobile integration, or user- friendly dashboards for traders and investors.

V LIMITATION

A. Lack of Interpretability in AI Models

As one main problem, most of the current AI models have a "black box" character. Because people tend not to know why models predict things, trust is hard to build so adoption is hard to grow.

B. Difficulty with Non-Stationary Data and Long-Term Trends

Traditional models, including LSTMs and CNNs, struggle to effectively capture long-term trends and adapt to the constantly changing, non-stationary characteristics of financial market data.

C. Inability to Adapt to Unforeseen Market Events and External Factors

Existing predictive models face difficulties in swiftly adjusting to sudden market shifts and comprehensively incorporating the complex interplay of various external factors (e.g., economic trends, national policies, investor psychology, company management capabilities, industry- specific changes) that heavily influence stock prices.

D. Difficulty in Modeling Intangible Assets

Financial experts find it challenging to accurately quantify and integrate the influence of intangible assets (like "know- how" or brand value) into stock market prediction models.

E. Lack of Model Interpretability

Most ML/DL models (like LSTM, GRU) act as black boxes— producing results without explaining why. This reduces transparency and limits their acceptance in finance where reasoning is crucial.

F. Dependence on Historical Data

Most models only *use* historical price and volume data and do not take current inputs and external triggers such as international news, economic data, or policy decisions, which are typically market movers.

G. Underuse of External Features

Models rarely integrate complex external factors such as inflation, GDP, consumer demand, or company fundamentals, which can significantly influence stock behavior.

H. Short Forecast Horizon

The majority of studies focus on daily or weekly predictions, offering little insight into long-term investment strategies or macroeconomic trend forecasting.

P. Limited Sentiment Integration

While sentiment analysis is occasionally used, it's often shallow (e.g., basic polarity from headlines). Advanced NLP tools like BERT or FinBERT are underused, and noisy social media data is difficult to interpret accurately.

Q. Single-Market Focus

Most models are trained and tested on single-country or single-index datasets, limiting their generalizability across global markets or sectors.

VI. CRITICAL ANALYSIS AND EVALUATION

1.Limitations of Traditional Deep Learning Models

Various papers do directly critique famous deep learning models like Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM). They identify that these models tend to face challenges in the capture of long- term trends and are not very effective at accommodating the non- stationarity of stock market data. This indicates that although trendy, these models might not be robust enough for the dynamic financial landscape.

2.Lack of Interpretability ("Black Box" Problem)

A significant and frequently raised concern is the opacity of many existing Artificial Intelligence (AI) models. The difficulty in understanding the internal reasoning behind their predictions creates a "black box" problem, which hinders trust and impedes the widespread adoption of these models in critical financial decision-making processes.

3.Inadequate Adaptability and Incomplete Factor Consideration

Existing predictive models are faulted for their inability to quickly accommodate unexpected market developments. In addition, they do not adequately account for the complex dynamics of different external forces, including national policies, investor irrationality (for instance, herd behavior), macroeconomic conditions, management capabilities of companies, and industry-specific changes, all of which significantly influence stock prices. There is also a perceived constraint in modeling the role of intangible assets like "know-how" and "trademarks."

4.Inconsistency and Methodological Challenges in Sentiment Analysis

Inconsistency and Methodological Issues in Sentiment Analysis. The use of social media sentiment in stock forecasting is questioned critically owing to varying outcomes in various studies, with some showing no forecasting ability and others weak or strong abilities. Sentiment analysis on social media is methodologically difficult thanks to concise text, misspellings, and rare grammatical structures. Also, earlier sentiment analysis studies did use relatively small datasets, and this has drawn some criticism. Reasoning is generalizability according to critics.

5.Varied Performance and Specific Model Weaknesses

Varied Performance and Specific Model Weaknesses Overarching observation is that not all stock forecasting tools in existence show good performance, which calls for ongoing evaluation. Certain models are also under questioning; for example, XG Boost was less accurate in one comparison, due to its vulnerability to input variable scale.

VII. JUSTIFICATION OF PAPER

1.Improving Prediction Accuracy and Robustness

A number of articles seek for to introduce and to assess new AI and ML models just like ANNs, LSTMs, CNNs, Decision Trees, Random Forests, XG Boost, and also Reinforcement Learning. These models are within improvements to stock price predictions' accuracy with dependability, which is very important for traders plus investors.

2.Dealing with the Complexity and Dynamics of Stock Markets

The research recognizes the complex dynamics of stock markets, such as the impact of many tangible and intangible variables, and attempts to develop models that can learn to handle unexpected market shocks and non-stationary data.

3.Examining and Benchmarking Varied Methodologies
The articles systematically study, contrast, and integrate machine learning to frequently determine deep learning models' advantages and limitations under stock forecasting scenarios plus offer perceptions for future studies and real-world application.

4.Addressing Specific Shortcomings of Current Methodologies:
They solve for essential limitations like the inability of existing AI models to be interpretable, the inability to track long-term trends, the complexities of integrating advanced external factors, and inconsistencies in applying alternative data *sources* such as social media sentiment.

5.Employ AI in order to foster finance.
These works improve current methods when applying AI to a complex finance prediction task. They suggest new architectures as well as approaches such as exploring sentiment analysis or combining NLP with deep reinforcement learning.

VIII. FUTURE RESEARCH ON PAPPER

1. Quantifying and Incorporating Intangible Assets
A specific research direction involves developing methodologies to better quantify and incorporate the impact of intangible assets (like brand value, intellectual property, or organizational know-how) into stock valuation and prediction models.
Conflicts resolve and sentiment analysis improves and since findings are mixed regarding whether social media sentiment can predict, researchers should research carefully on a large scale in the field later. The methods of natural language processing or NLP must be improved upon. More valid sentiment indicators can be obtained via coping with the noise, conciseness, as well as grammatical quirks of social media language.

2. Comprehensive Evaluation and Benchmarking
There is an ongoing requirement for large-scale and methodical comparative research on various stock forecast models and software tools, employing diverse data sets and meaningful performance measures, in order to make unambiguous benchmarks and determine the best methods under different market conditions.

REFERENCE

[1] G. Zhang, B. E. Patuwo, M. Y. Hu, "Forecasting with artificial neural networks: The state of the art", Int. J. Forecasting 4 (1998) 35-62.
[2] Arnim B., and Pat Langley, 1997. Selection of relevant features and examples in machine learning. Artificial intelligence 97(1-2): 245-271
[3] Cha Uen Hue and Shichun Yng, 2006. Comparison of support vector machines and back propagation neural networks in forecasting the six major Asian stock markets. International Journal of Electronic Finance, 1(1): 49-67.
[4] Arnim B., and Pat Langley, 1997. Selection of relevant features and examples in machine learning. Artificial intelligence 97(1-\2): 245-271.
[5] E. F. Fama, "The Behavior of Stock Market Prices", J. Bus. Vol. 38, no. 1 (pp. 34-105), 1965.
[6] Fama E. F. "Two pillars of asset pricing". American Economic Review, 80(4), 1141-1165.
[7] Ciro L. O. Rocha T (2002). Cellular neural networks and neural computing. Cambridge University Press, Cambridge.
[8] R. S. Sutton, A. G. Barto. "Reinforcement Learning: An Introduction". MIT Press, (2018)
[9] Alexander, C (2009) Market risk analysis: value at risk model volume IV edition. Chichester, England: Wiley
[10] Milan S. N., Muhammad U. N., Usman J. Q. Relationship between Economic Growth and stock market development. Asian Journal of Business Management, 10(1), 4-16.
[11] Chen T., H. T. Beijing M., et al., 2016. XG Boost: extreme gradient boosting. R package version 0.4-2, 2015, 1(4): 1-4.
[12] E. F. Fama, "The Behavior of Stock Market Prices", J. Bus. Vol. 38, no. 1 (pp. 34-105), 1965.
[13] Fama E. F. "Two pillars of asset pricing". American Economic Review, 80(4), 1141-1165.
[14] S. R. Moore, S. Syed, and D. E. Brown, "Hierarchical deep convolutional neural network”
[15] R. Karim, M. K. Alam, and R. Hossain, "Stock Market Analysis Using Linear Regression and Decision Tree Regression," in Proc. 2021 1st Int. Conf. Emerg. Smart Technol. Appl.(eSmarTA), 2021,doi:10.1109/ESMARTA52612.2021.9515762.
[16] N. Tripathy stated “Stock Price Prediction Using Support Vector Machine Approach” during the

International Academic Conference on Management & Economics in 2019.

[17] Y. Wu, "Stock Price Prediction Grounded on Simple Decision Tree Random Forest and XG Boost," BCP Business and Management, 2023.

[18] H. Xu, "Stock price prediction with decision tree classifier and LSTM network," Proceedings of the 2023 International Conference on Machine Learning and Automation, 2023, doi: 10.54254/2755-2721/37/20230512.

[19] M. Sui, C. Zhang, L. Zhou, S. Liao, along with C. Wei authored "An Ensemble Approach to Stock Price Prediction Using Deep Learning and Time Series Models," Preprints.org, 2024, doi: 10.20944/preprints 202409.2077.v1 [19].

[20] T. Kozdraj, Acta Univ. Lodz., "USING ARTIFICIAL NEURAL NETWORKS IN ORDER TO PREDICT STOCKPRICES." 2009, Folia Oeconomica, vol. 225.

[21] S. Mehtab along with J. Sen wrote "Stock Price Prediction Using Convolutional Neural Networks on a Multivariate Time Series." It was published in August 2021.

[22] "Long Short-Term Memory and Gated Recurrent Unit for Stock Price Prediction," by A. Rahmadeyan and Mustakim in Procedia Compute. 2024, Sci., in vol. 234, on pp. 204-212.

[23] P. Rani et al. wrote "Stock Price Prediction Using Reinforcement Learning" for Advances in Clever Systems and Computing, 2022, doi: 10.1007/978-91-16-2597.

[24] A. L. Awad, S. M. Elkaffas, also M. W. Fakhr said "Stock Market Prediction Using Deep Reinforcement Learning" within Appl. Syst. Innof., vol. 6, no. 10.3390/asi6060106 with doi as 106 in 2023.

[25] H. Li, C. H. Dagli, also D. L. Enke, in Proc. "Short-Term Stock Market Timing Prediction Under Reinforcement Learning Schemes." IEEE Internal. Symp. Approx. Dynamic Program. Reinforcement Learn., Honolulu, HI, USA, doi: 10.1109/ADPRL.2007.368193, 2007.

[26] S. Mohan et al. in Proc., "Stock Price Prediction Using News Sentiment Analysis" at 2019 IEEE Fifth Int. Conf. Big Data Comput. Service Appl. (BigDataService), in 2019, doi: 10.1109/BigDataService.2019.00005.

[27] "Feature Engineering for Stock Price Prediction," by R.M. Nabi, and A. Abdi, and then S. Saeed, Int. J. Adv. Sci. Technol., vol. 29, no. 12s, 2020, in pp. 2486-2496.

[28] E. Sharkey and P. Treleaven wrote "Comparison of BERT vs GPT" on arXiv:2405.12990. It is listed in the cs category. CL], May 2024.

[29] "Federated Learning Improved MLP-LSTM Modeling within an Integrated Deep Learning Pipeline for Stock Market Prediction," by J. Kumarappan et al., Int. J. Comput. Intell. Syst., vol. 17, no. 267, in 2024, with doi: 10.1007/s44196-024-00680-9.

[30] M. S. Chowdhury et al. "Deep Learning Models for Stock Market Forecasting: A Thorough Comparative Analysis" J. Business Management Studies, date unknown.

[31] D. Dave, G. Sawhney, and V. Chauhan, arXiv, 2025, doi: arXiv:2502.15853v1, "Multi-Agent Stock Prediction Systems: Machine Learning Models, Simulations, and Real- Time Trading Strategies."